Assembling Algorithmic Decision-Making under Uncertainty: The Case of 'Edge Cases' in an Open Data Environment

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Abstract

Algorithmic decision-making is rapidly evolving as a source of data-driven competitive advantage with important implications for analytical practices in multiple settings. Despite the ambitions for algorithmic and intelligent technologies, however, the requirement for quality data input to the algorithm poses a significant challenge for its actual adoption. The trend towards open data might bring additional challenges such as strategic gaming and distortion of meaning. To address this problem, we draw on a two-year long qualitative case study of a firm in international maritime trade to understand the role of uncertainty associated with open data upon the uptake of a novel algorithm. We combine an uncertainty and assemblage perspective to unpack the arrangements by which the organization configures relations of humans and machine to mitigate this problem. We highlight the phenomenon of edge cases as a key challenge for automation and propose that an assemblage of augmentation and automation allows a dynamic arrangement that support the introduction and organization of algorithmic decision-making under uncertainty.

1. Introduction

Artificial intelligence (AI) including data analytics and learning algorithms is evolving as a key priority for decision-making [1] and is already transforming predictive practices in domains such as medicine, law, finance, and transportation. Despite the growing interest in AI among IS (Information Systems) scholars and practitioners, however, there is a continuing gap between the ambitions for AI and its actual adoption [2]. A significant challenge and probable reason for this gap is that AI places great demands on the availability of quality data input [3, 4]. Data not only tend to be heterogeneous and unstructured [5], they tend to be controlled by certain organizations [6], be open in the public domain or becoming a commodity [7, 8, 9]. Whereas control over data may be a source of competitive advantage [10], mandated openness can undermine competitiveness to the extent that competitors or regulators get hold of strategically sensitive information [11, 12]. In such environments, increased openness and transparency can give rise to 'gaming' of the data [8, 13, 14] and 'distortion of meaning', with performative consequences for analytics and decision-making [8]. Despite the recognition that the uncertainty associated with data represent a significant challenge to the adoption of AI [3, 15, 16, 17], knowledge of what constitutes a problematic situation and how its resolution involve arrangement of humans and algorithms [4], is still limited. Therefore, understanding the uncertainty associated with open data might have important implications for how organizations can "efficiently identify and handle many types of noisy data" [4] and thus organize upon the introduction of algorithmic decision-making.

In this paper, we examine these questions in the context of mandated data openness and explore organizational arrangements for mitigating the uncertainty that follows the strategic interests over externally sourced data. Our research question thus is: *What problematic situations in open data environments and types of algorithmic decision-making involve division of labor between humans and algorithms?*

To answer our research question, we draw on a two-year long qualitative case study of a brokering firm in international maritime trade. The firm's analytics division acquired near real-time data from the Automatic Identification System (an open, global information infrastructure retrieving and transmitting detailed data on vessel movement) via satellites and adopted a classification algorithm to support the prediction of ship behavior and, in turn, global trade on oil. In this case, classifications of data input were uncertain due to 'edge cases' exemplified by ships (i.e.

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the observed) gaming or distorting data about their actual activity at sea. Through drawing on the phenomenon of edge cases in this context, we are interested to contribute an understanding of what constitute a problematic situation and the division of labor between humans and machines that emerges as a response to this [4].

The concept of edge cases comes with different meanings, but can generally be understood as cases that involve input values that require special handling by the system. We further understand uncertainty associated with open data edge cases as problematic "situations which involves unknown or imperfect information" [16, 21] that constrain the adoption of algorithmic decision-making, because "uncertainty refers to the degree to which the future states of the environment cannot be accurately anticipated or predicted due to imperfect information" [22].

The paper is structured as follows. First, we review recent literature on data-driven and algorithmic decision-making with an emphasis on task automation, augmentation, and assemblage approaches. Building on this background, we highlight the phenomenon of edge cases and combine uncertainty and assemblage perspectives to develop our analytical frame. Next, we outline our case study research approach followed by a brief background description of our case from the international maritime trade. In the case findings section, we illustrate four 'edge cases' and the case organization's responses to these as it sought to introduce algorithmic decision-making into the fabric of the organization. In the analysis and discussion, we elaborate on the relevance of assemblages for evolving algorithmic decision-making in the context of open data and uncertainty.

2. Related research and framework

2.1. Automating, augmenting, and assembling algorithmic decision-making

Newell and Marabelli [1] take *data-driven and algorithmic decision-making* to comprise vast data that are processed by algorithms with the aim of predicting objects' behavior based on their current or past behavior. Similarly, Faraj et al. [23] refer to learning algorithms as "machine learning, computation, and statistical techniques .. [that] rely on large data sets to generate responses, classifications, or dynamic predictions that resemble those of a knowledge worker". *Prediction*, here understood as using information you do have to produce information you do not have [15], then, constitutes a fundamental task of algorithmic decision-making systems and the learning algorithms on which these are based [24].

Following an information processing and task perspective, von Krogh [4] suggests that while such AI systems entail task input in the form of data and task processing by algorithms, task outcomes involve either conclusions based on available data (i.e. decision-making) or alternative courses of action to resolve a problem (i.e. problem-solving). Drawing on this task approach, Rai et al. [25] propose that AI systems do not only comprise *task substitution* by which AI automates or replaces tasks that human used to perform. They also comprise *task augmentation* where humans and AI complement one another to perform a task; *and task assemblages* in which humans and AI are dynamically brought together as an integrated unit to perform an emergent task [25].

The Information Systems (IS) and organization literature has already recognized an augmentation approach [19, 23, 25, 26]. For example, recent empirical research has showed that organizations bring humans in the loop of the algorithm to evaluate cases that are unknown to the algorithm and to improve the accuracy of the algorithm [27]. Similarly, in interactive machine learning and active learning systems [28], an unknown or unconfident task can be delegated to a human(s) who manually labels (or annotates or classifies) it, and then feed it back to the algorithm for learning experience.

While there is a growing interest in algorithmic decision-making, however, organizational research on the dynamic configuration of humans and algorithms upon emergent, problematic tasks, is still limited. Such inquiry might benefit from the collection and analysis of rich material on problematic situations [4]. In the following we therefore adopt edge cases as a sensitizing concept and take human-algorithm collaboration as the central analytical component.

2.2. Edge cases, uncertainty, and assemblages

Edge cases, when framed as "situations where little data exists" [33], relate to *uncertainty* which refers to not having enough information [29]. When taken as "data that are encountered for the first time" [3], edge cases pertain to *ambiguity* which denotes "not having a conceptual framework for interpreting information" [29]. Furthermore, in big data setting we assume that edge cases also concern *complexity* - having to process more information than you can manage or understand; and *equivocality* - having several competing or contradictory conceptual frameworks [29]. A framework in this sense can include both machine learning models and human cognitive frames that rely on some system of classification. In the case of equivocality, then, algorithms and humans can have contradictory frameworks that may or may not complement one another.

Zack [29] further argued that machines are more appropriate for handling decision problems characterized by complexity and uncertainty, whereas humans are better suited for handling ambiguity and equivocality. In this view, problems of uncertainty and ambiguity can be resolved by acquiring more information and interpretative frames. However, such acquisitive processing strategies in turn give rise to problems of complexity and equivocality. Problems of complexity and equivocality, on the other hand, might be resolved by restricting existing information and diverse interpretations. However, such restrictive processing strategies appear to come at the expense of the data scale effects underpinning the promises of automation underpinning 'big data' and AI systems. Thus, edge cases associated with uncertainty and complexity emerge as subject to analysis and automation; while ambiguity and equivocality be subject to interpretation and augmentation. However, because the resolution of one decision problem, e.g., equivocality, can trigger another problem, e.g., uncertainty [29], there is need to understand the dynamic reconfiguration of the problem-solving structure.

Rather than taking algorithmic decision-making as a predefined and stable phenomenon [cf. 18], we are interested to examine the situations which configurations of algorithmic decision-making spring from [19]. We draw on a notion of assemblage that views humans, algorithms, data and practices as "heterogeneous components interrelated to one another in such a way that brings about evolving patterns of actions" [20]. "Offered in part as replacements" [18] for the input-processing-output view and the separation of human and machine, then, Suchman's conception of (re)configuration suggests that an assemblage lens is useful to "expand the space of interaction from the interface narrowly defined to the ambient environments and transformed and transformative subject-object relations that comprise lived experience of technological practice" [18]. Here, avocation denotes arrangements and affordances of through which humans are hailed to enter a technological assemblage; invocation denotes actions that define the events that effect changes to the assemblage; and evocation denotes the material changes that result and in turn comprise the possibility of subsequent avocations [18].

3. Case selection and research methods

We conducted an interpretive qualitative case study [30] of ShipBroker over two years, beginning in September 2017 and ending in October 2019. ShipBroker (dubbed for anonymization), a global shipbrokering firm since the mid-1800, operates a network of >10 offices worldwide and employs several hundred employees. The firm intermediates logistics and commodity freight such as oil and gas on behalf of cargo owners, ship owners and charterers. ShipBroker's services rely upon detailed research and analysis on current market developments and seaborne trade. Here, a mission-critical data source is the Automatic Identification System (AIS), a global communication and tracking system which is used for exchange of maritime navigational information between AIS-equipped terminals. Since 2002, the AIS is mandatory installation for international ships (or vessels) with 300 or more gross tonnages. The AIS works by retrieving GPS coordinates from satellites and transmitting data on ship behavior and qualities to nearby stations (including ships, vessel traffic services, buoys) via VHF radio signals. ShipBroker relies on AIS data to track ships and ports and in turn construct aggregates on global trade.

Initial access sprung from an existing development project between ShipBroker and an enterprise software company where the first author was employed during his PhD. Further access was negotiated between the author and the firms' top management in spring 2017 and allowed us to take part in both strategic and operational activities with ShipBroker's research department which specializes in 'shipping intelligence', trade and freight analyses. Our role and intent as researchers in the field were clearly communicated to the informants, and observations and interviews were based on informed consent and confidentiality about business-critical information. We have by purpose anonymized the names and gender of the subjects involved in our research.

Our main method was participant observation, complemented by informal interviews, conversation, and reviews of documentation. Participant observation were undertaken in a total of 39 meetings and during a two-week-long design workshop in early 2018. The meetings were mainly on-site and lasted between thirty minutes and five hours, with an average duration of 104 minutes. During our fieldwork, we regularly conducted informal interviews and conversation, including in-person meetings, lunch meetings, face-to-face conversations in the field as well as over telephone, to follow up and verify our observations. We avoided recording our observations and conversations so as to ensure openness and trust, and instead focused our attention on taking notes during the field work and wrote these out into memos and narratives shortly after the meetings. We examined documentary sources including company PowerPoint-based market analyses, Excel spreadsheets of ship voyages, customer contract excerpts, trade journal articles, newspaper articles, web sites, ship tracking software, and code such as MySQL queries. We were also given a company chat and email account on which we regularly conversed with our key informants.

Conducting the data collection in tandem with data analysis allowed us to recursively iterate between emerging empirical material and theoretical concepts in the datafication, big data analytics, business intelligence, and AI streams within the IS and organizational research literature. To guide our analysis, we adopted a narrative and visual mapping approach [34]. The narrative approach consisted of writing theoretical memos to gradually develop more detailed narratives and vignettes from the data. We further mapped and organized our material into a broader set of themes [35] such as “obscuring”, “secreting”, and “going dark”. Drawing on the narratives and themes together with our informants, we set boundaries for our analysis and focused attention on material revolving around ‘edge cases’. We complemented this with the visual mapping approach to generate temporal data bases, which allowed identification of relevant, more abstract themes and relationships as we explored data-theory links in light of new empirical material.

4. Case findings

4.1. Encountering edge cases

In fall 2017, a group of executives—the CEO and CDO (Chief Digital Officer) at ShipBroker and the CEO at the enterprise software provider—gathered to discuss potential solutions to strategic challenges and changes in the competitive market. Due to rapid digitalization and adaptation of AIS data, the global maritime trade industry had been subject to commoditization and symmetrization of mission-critical information. Data on the activities of the global trade fleet, which traditionally had been advantageous to the brokers (according to one senior analyst), was now becoming available and accessible across the value chain. However, ShipBroker was not only facing long-term risks of disintermediation, it was also exposed to secreting and obscuring of ships’ digital traces, such as tampering with data on the movement, destination, and draught level of ships’ hull. Recurrently referred to as “going dark”, “fake news”, and "teleporting” among our informants, these data quality issues (called edge cases) constituted a significant challenge to the analysts who relied on accurate and timely data to intermediate exchange of logistics between ship and cargo owners.

Towards the end of the executive meeting, a new strategic direction had emerged. First and foremost, ShipBroker sought to use smart algorithms to turn external and internal trade data into a strategic asset, to support human decision-making, and, eventually, drive competitive advantage. The question of how to integrate extant digital work with the development of algorithmic decision-making in face of problematic data input, however, remained an open question. On the backdrop of these conditions, we next illustrate four ‘edge cases’, and the resolutions to these, that were involved in the work of introducing algorithmic decision-making into the social fabric of the organization. Table 1 summarizes the edge cases, their nature of uncertainty, and the responses to these.

Table 1 Summary of edge cases, uncertainty characteristics and responses

Edge cases	Nature of uncertainty and responses
The ‘fake news’ cases	The decision problem was characterized by complexity where there was a diversity of spellings/meanings in the destination fields, and equivocality where the data and its meaning could be interpreted in multiple ways e.g., avoiding pirates or distorting for commercial gain. ShipBroker’s resolution entailed collective human auditing of the algorithmic outcome to update the framework and altering of the algorithm’s rule set for normalization of choices.
The withholding cases	The decision problem mainly was characterized by uncertainty because there was not enough information to describe a current state or to predict future states.
The going-dark cases	The decision problem was characterized by uncertainty where there was not enough data to describe a current state, and ambiguity since there was no sufficient explanation for the event. ShipBroker’s response involved acquiring contextual data and interpretation from domain experts, and then altering the algorithm to do ‘guesswork’ (i.e. prediction).
The teleporting cases	The decision problem was characterized by ambiguity and equivocality because there was either no framework to explain the event or multiple explanations. ShipBroker’s response entailed deep human-to-human discussions, however, with no confident explanation.

4.2. The ‘fake news’ cases

In one of the many meetings that were focused on evaluating the algorithm, a team of participants collectively and carefully examined algorithmic output: ship movements, their voyage patterns, and drought change at certain ports. The problem case was malicious or erroneous data records on the activity of a certain ship. One possible explanation to the inconsistencies was technical: that another ship had interfered with its AIS signals. But the more likely explanation was human: that the ship operator had tampered with the data transmission. Typically, for any voyage ship operators must manually type into their AIS transponder information about its destination, among other fields. For example, on several occasions various members of the team referred to a ‘*thousand variations of the port of Singapore*’ which the algorithm had picked up. To counter this problem, the data scientist on the team set out to encode all kind of various portmanteaus, abbreviations, acronyms, etc. related the port of Singapore and subsequently collected any new variation that the team encountered throughout the process of evaluating the algorithmic outcome. Arrays of port spellings were then integrated into the algorithm’s ‘mapping function’ so that it could normalize such instances going forward. While this specific case made a reference point in subsequent meetings, consensus was that there generally are incentives for ship operators to obscure mission-critical data. This type of problem, often referred to as “fake news” or faking destinations, was frequent. Accordingly, the process of revising data and updating the algorithm had to be repeated for the reminding ports that accepted ships in this segment.

4.3. The withholding case

“*This just arrived on the desk of one of the senior brokers*”, the CDO uttered while putting a print-out onto the office desk. He was referring to a client contract that specifically described conditions on the timing for dissemination of voyage data. One client had intentionally requested that information on its ship’s whereabouts was to be withheld. More specifically, by caps lock wording in the contract the client had requested that by the time the vessel was going to pass Skew (on the Northern coast of Denmark) all involved parties should wait as long as possible until transmitting the true destination of the ship. The ship was departing from Russia with hundreds of thousands of tons of crude oil and heading for the southern US coast, but, apparently, the ‘observers’ did not need to know about this until there was no doubt about its actual destination.

This situation somewhat confirmed extant presumptions that strategic withholding of voyage data is not an abnormal practice among competitors and the fleet in general. Thus, the situation added to the development agenda that also contract data should be systemically collected and consolidated with AIS data to augment timely decision-making. Nevertheless, the speed at which AIS data was collected and trade files were produced was deemed important.

4.4. The going-dark cases

Ships “going dark” was another imminent issue in the intelligence augmentation process. This problem of incomplete or missing data on ship activity became apparent in multiple meetings which dealt with a reoccurring case—dubbed the ‘South Korean issue’ or the ‘Korean case’ by the team members—in which a substantial number of ships voyaging by the Korean Peninsula suddenly yet continuously went missing from the interactive monitoring tools. Unfortunately, this resulted in distorted data sets. As the digital executive explained to an external consultant: *“When a ship is approaching Korea, it always goes black, so we need to use algorithms to determine which port the ship actually goes to.”* In addition, the project management team approached the satellite operator from which ShipBroker pulled AIS data to ask for potential explanations. However, the satellite operator answered that this was a general issue that was out of their control and that there was no immediate solution to it. Instead, the development team assumed that this problem could be resolved by instructing the algorithm to do ‘guesswork’ about the vessel movement based on historical data on voyages.

4.5. The teleporting cases

“How can it possibly be that a vessel that was located by the coast of Texas yesterday is observed in Middle East Gulf at the present”, the CDO confronted the development team. This is physically impossible, so why is it the case, the team wondered. Issues like this, referred to as ‘teleporting’ among our informants, were rather frequently observed during the many evaluation meetings focused on scrutinizing algorithmic outcome. The data scientist and the rest of the team were scratching their head on how to solve these abnormalities because it debased the trade files. With no ready solution at hand, investigations into how the algorithm could be designed to handle such

teleporting issues were started. A couple of diagnosis were suggested. The prevailing explanation was that some ships might be equipped with duplicate identification numbers. It was speculated that this has historically been done for cost saving reasons. These cases of abnormal output represented edge cases that required cycles of human evaluation leading to multiple yet uncertain explanations for the event.

5. Analysis and discussion

5.1. Assembling human and algorithmic decision-making under uncertainty

Recent research has described how organizations bring humans into the loop of the algorithm to augment and improve the accuracy of analysis [27]. However, it remains uncertain how such augmentative efforts can be efficiently integrated with the opportunities for speed and scaling provided by automation, under conditions of uncertainty. We build on this to explore how organizations can achieve a balance between the two in face of 'edge cases' as a significant challenge for achieving accurate algorithmic decision-making based on open data.

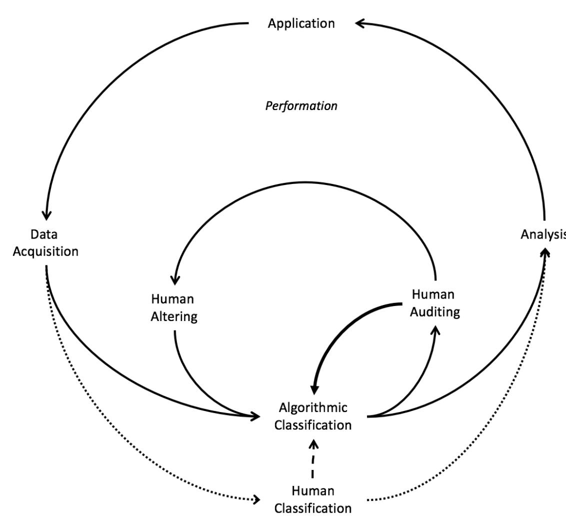

Figure 1 Human-in-the-loop pattern for augmenting analytics (adapted from [27])

Most notably, we observed that preexisting assemblages come to serve as backdrops to new assemblages and comprise both the notions of automation and augmentation. A key reason for the emergence of this composite assemblage was the need to overcome the challenges of uncertainty that come with the input of open data (i.e. edge cases).

Towards their vision of achieving automated analysis and algorithmic decision-making (the inner loops in Figure 1), ShipBroker commenced from a manual practice of computer-supported data analytics (the outer loop) in which the mundane handling of edge cases was considered to cause a bottleneck for achieving timely analyses. As a response to this bottleneck, ShipBroker's development team introduced a classification algorithm to automate and speed up the classification work.

Following the introduction of the algorithm, we observed that the new practices of human auditing – evaluating the algorithmic output against a ground truth; and altering - changing the parameters and rules of the algorithm were necessary to improve the accuracy of the algorithm. However, this new work also limited the performance of the system compared to what a more automated approach would have offered.

Yeow and Faraj [20] note that preexisting assemblages serve as a backdrop to new or changed assemblages, and that the performance of the focal assemblage depends on its surrounding assemblages to co-perform. In this case, we see that the outer 'human assemblage' (i.e. data acquisition-human classification-analysis in Figure 1) is linked to and serves a backdrop to the mid 'automation assemblage' (data acquisition-algorithmic classification-analysis), which in turn serves as a backdrop to the inner 'augmentation assemblage' (algorithmic classification-auditing-altering). Here, the main purpose of the latter assemblage was to augment the algorithm so as to make it perform upon encounters with edge cases. In line with Yeow and Faraj's performative assemblage, our observations suggest that parts of the assemblage (human classification) could be extracted from a preexisting assemblage (the human assemblage) to another (the augmentation assemblage) creating different relationships, here seeing that the work of human classification was repurposed to provide a ground truth measure to the auditing of edge cases. Similarly, the work of human auditing could be extracted from the augmentation assemblage to the center-most 'training assemblage' (algorithmic classification-human auditing).

While these arrangements correspond with the input-processing-output task flow [4] (from left to right in Figure 1), the assemblage approach of Suchman [18] allowed us to also capture where humans are included (avocation) in the assemblages to deal with problematic situations (invocation) and provide auditing and altering of the algorithm (evocation). Here, altering was mainly concerned with ambiguity and equivocality problems as new frameworks were developed and introduced to the algorithm. Auditing entailed dealing with uncertainty and complexity problems, which could be resolved by providing the algorithm with (training) examples, as congruent with the idea of interactive machine learning algorithms [28].

The reconfiguration of this nested assemblage of humans and the algorithm, augmentation and automation processes, is dynamic in the sense that the organization can have one or more of the assemblages to co-perform more or less concurrently [20]. For example, the (outer) manual/human assemblage can run in parallel to the augmentation and automation assemblages to allow continuation of 'business as usual' while also enabling design and use of the algorithm. The assembling of algorithmic decision-making thus appears to be temporally emergent and dependent on the former assemblages. This example of a trajectory of algorithmic decision-making can give researchers and practitioners a clue about the evolving and relational problem-solving arrangements which machine learning and AI spring from [19].

5.2. Implications for algorithmic decision-making in open data environments

Much of the literature on algorithmic decision-making address cases where the underlying data is under organizational control. The issues with data quality can then (in principle) be improved given enough efforts. The situation is different with externally sourced data. Discussing the strategic implications of using available social media data, Constantiou and Kallinikos [5] emphasizes that these data are unstructured, heterogeneous, agnostic, and trans-semiotic. They argue that this makes the application of this data for strategic purposes more challenging.

Our case relates to such external and highly variegated data, however not from social media, but from geospatial data shared via satellites and a global information infrastructure. Here, the issues of data quality and veracity are not "fixable"; this is a problem for which the organization must put remedies in place so that it can deal with the problem on a continuous basis. This resembles the challenges encountered in data-intensive, but physically inaccessible contexts such as sensor-rich offshore installations that are remotely monitored via data streams and algorithmic processing [31]. The employees do not know whether the data are or are not trustworthy, and they need to deal with this, e.g. through visualizing data in order to detect anomalous patterns in confounded data, sorting out whether the signal is impacted by interferences, and collectively sharing narratives that serve as relevant background information, e.g., on previous behavior of certain wells [32].

6. Conclusion

The use of open and externally sourced data as input to algorithmic decision-making comes with uncertainty issues. Introducing an algorithm and automatic processing may add new challenges. The initial expectation is often that the algorithm should help resolve these data issues, however, the algorithm itself is often perceived to be opaque and 'black-boxed'. The concerns about data quality and algorithmic opacity have generated recommendation for algorithmic audits and other human control mechanisms with the purpose to oversee and mitigate undesired outcomes. As these mechanisms depend on humans to both control and augment the algorithm, they are often denoted "human-in-the-loop" setups and defined by augmentation work. We believe that the notion of performative assemblage provides a useful perspective for further examining what the interplay of automation and augmentation entail for new ways of organizing algorithmic decision-making under conditions of uncertainty.

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